Raise The Bar:
Barbell Path and Velocity Tracking Mobile App for Weightlifting

Neython Lec Streitz

`nlecstreitz@oxy.edu`
Occidental College

1   Problem Context

From the average gym-goer to the elite professional athlete, the ability to track and monitor training is key for supporting safe and effective workouts. Specifically for intermediate to advanced athletes, exercise efficiency and load management becomes crucial for maintaining long-term performance improvements. The purpose of this mobile app is to provide an accurate, useful, and accessible method of tracking the path and velocity of a barbell during resistance training exercise. Through the use of this app, athletes and coaches can objectively track their range of motion and the intensity of their workouts.

Put simply, bar path refers to the range of motion of the barbell during an exercise. Bar path tracking thus, tracks the time and distance of the barbell during a specific lift. By optimizing the bar path for a given exercise, an athlete is able to pinpoint weak points in their movement and generate better efficiency overall. Especially for beginners, bar path is an incredibly helpful tool for improving and visualizing exercise form.

For the more advanced, velocity tracking provides even more granularity. Typically, exercise loads are prescribed using percentage-based methods. For example, a coach might make their athlete perform 5 sets of 5 repetitions using 70% of their 1-rep max. Percentage-based training has a long history of being an effective approach for resistance training design. Recently, Velocity Based Training (VBT) has emerged as a contemporary method of resistance training design, using the velocity of the barbell during an exercise to supplement and inform training decisions.

VBT is useful because it allows for more athlete-specific load (weight amount) and volume (repetition amount) prescriptions [22]. For one, it can gauge an athlete's current fatigue levels by comparing velocity in previous sessions. This practice is known as autoregulation, where an athlete can pull back on high fatigue days and push harder on days they are feeling fresh. Secondly, VBT allows coaches (or self-lead gym-goers) to assign training loads that deliver more precise and objective levels of effort and fatigue. Some athletes have difficulty doing higher repetition work, whereas others see sharp drop-offs near their one repetition max. In the percentage-based approach, set and repetition recommendations do not account for this variability [1]. With all that in mind, bar path and velocity metrics serve as a way to standardize technique for a beginner, and for the advanced, give biofeedback in real-time and enable the design of athlete-specific programs.

Currently, there exists various hardware and software-based approaches to tracking bar path and velocity. This includes hardware devices like linear position transducers and 3D motion analysis systems, as well as video-based smartphone apps. However, using hardware to track velocity is expensive and inaccessible for the majority of regular gym-goers and even for advanced athletes. Furthermore, most smartphone apps show poor accuracy and clunky design [14, 11]. Thus, our app is in a position to improve on the accuracy and design of existing smartphone apps, while circumventing the money and infrastructure needed for hardware-based approaches.

2   Technical Background

At its most basic, the question at hand is how we can track, and ultimately display, the position and rate of change of a dynamic object in real time. Thus, this project is one in the realm of computer vision (CV), or, how computers interpret the visual world. At a glance, the technical components of this project includes object detection and object motion tracking.

2.1   Object Detection

To begin, there needs to be a way to detect the barbell within the frame of the video. The main goal of object detection within CV tasks is to identify and draw boundaries around objects in a given image or video. State-of-the-art approaches utilize deep-learning methods and neural networks to perform object detection. To this end, there are typically two main parts to object detection with deep-learning. Firstly, the image or frame passes through an encoder that extracts statistical features used to locate and label objects. Then, the encoder's outputs are passed through

a decoder that predicts the boundaries and labels of each of the objects.

An existing network architecture is usually the encoder used for object detection. Two of the most common network architectures are VGG and ResNet [19, 7]. However, these networks are simply too large for resource constrained devices like smartphones. Developed by Google, MobileNet is an encoder specifically made to work on mobile devices [9]. It functions by employing depthwise separable convolution, a process that decreases the amount of parameters in the network, making it less resource intensive.

Common decoders used for object detection applications include Faster R-CNNs and You Only Look Once (YOLO) [18, 17]. While Faster R-CNNs delivers great accuracy, it suffers in overwhelming complexity and slow speed. YOLO has the opposite problem, as it provides speed but lacks in accuracy. Google's Single Shot Detectors (SSD) aims to provide a middle ground [13]. SSD works by laying a grid of anchor points over the input image then overlaying boxes of multiple shapes and sizes at each anchor point. The model then predicts the likelihood that the object to be detected exists within the box, changing the boxes to fit the object as best as possible. The lower likelihood boxes are pruned away, leaving a best prediction of the boundaries of the object.

By combining MobileNet and SSD, smartphones are capable of supporting deep learning-based object detection. Having said that, the MobileNet and SSD combination supports the detection of 20 different objects, none of which are barbells. Given that the process of training a network to specifically detect barbells is likely very GPU intensive, slow, and unreliable, my project takes advantage of the relative ease of tracking a pre-specified color and shape. By using a sticker, post-it note, or simply painting the end of a barbell, we can set the color of the barbell apart from the rest of the video frame. Combined with the fact that barbells are standardized sizes, the combination of color and shape to object detect, essentially turns the barbell into a contour.

A contour is a well-defined boundary with matching color or intensity within. To allow for contour detection, the image or video frame is first converted to grayscale. Next, binary thresholding is applied, converting the image to black and white by setting only the borders of the object white and the rest black. A contour algorithm is finally applied to identify the borders, and if needed, draw them out over the original image. The algorithm simply detects sharp changes in intensity of color throughout the image and marks it as a border. Contour detection is a much simpler process, allowing me to maintain accessibility and ease-of-use, without the need to train a neural network.

2.2 Object Tracking

In essence, the velocity of a barbell is simply its directional movement over time. To get the barbell velocity, it is necessary to track it throughout the frames of a video. In the case of a barbell, we will be engaging in Single Object Tracking (SOT).

Typical problems in object tracking include occlusion, detection speed, and spatial scale variation. Occlusion is simply when objects are so close to each other that they appear to be one merged object. Luckily, supporting occlusion is not something we need to deal with, as the barbell will almost always be in an open and unimpeded space. Similarly, because we are tracking the barbell side-on, almost as if it was two-dimensional, there is little variation in object scale. Detection speed is certainly an issue, but because this is a contour detection problem, there already exists fast and efficient techniques.

There are a variety of neural network approaches to object tracking, including BOOSTING Tracker, MIL Tracker, and KCF Tracker [6, 4, 8]. These approaches each have their benefits and downsides, typically balancing general accuracy, occlusion support, lighting and viewpoint change, and error detection.

For the purposes of this project, tracking will involve repetitively updating the camera and calculating the previous pixel position with the current. Knowing the size of the end of the barbell, the amount of pixels occupied by the barbell in the frame can be used to track the movement of the barbell throughout the video. A list-like data structure such as the *deque*, provides quick enough pops and appends to maintain and retrieve the previous positions of the barbell. Due to the frame rate of modern smartphones, this process should be quick enough to accurately track the position and velocity of the barbell.

3 Prior Work

As mentioned before, there currently exists a variety of hardware and software-based methods of tracking barbell path and velocity. While the market is fairly large, there are only a handful of devices, systems, and apps that have been studied in sports science literature. The studies that have been done, mainly evaluate the reliability, ease-of-use, and practicality of these technologies.

As far as hardware-based approaches are concerned, linear position transducers, also known as linear encoders, are considered the gold standard for velocity tracking. These devices clip onto the barbell and have a cable moving in and out of the device. Examples of linear encoders available on the market include Vitruve, T-Force, and GymAware. These companies also include or offer paid mobile apps for synchronization with their devices. All three of the listed de-

vices have been validated by studies in sports science literature [14, 20, 15]. However, great accuracy comes at a price, as linear encoders are expensive and inaccessible. The lone GymAware device comes in at over $1,995, with accompanying software starting at an additional $495 minimum. Vitruve is a cheaper option, yet still comes in at around $397 for the device and mobile app. One more thing to note is the potential for damaging the devices because they must remain directly under the barbell. This is especially problematic for intensely dynamic movements like the Olympic lifts.

As far as hardware-based approaches to path tracking, there are no current devices on the market with the express purpose of visualizing barbell paths. That's not to say that three-dimensional motion capture camera systems can't and haven't been used to track bar path and velocity [15]. Yet, like linear encoders, camera systems are costly and involve infrastructure not accessible nor feasible to set up for the average gym-goer. Nonetheless, the reliability of these devices means they are often used to test the validity of novel velocity trackers, like mobile apps [15].

For software-based approaches, specifically, mobile applications, there are multiple offerings on the market. Examples of apps that include both bar path and velocity tracking include MyLift, IronPath, and BarSense. Of those, MyLift and IronPath have been studied in the literature. Markedly, studies have concluded that both MyLift and IronPath are not reliable tools for the measurement of barbell velocity. Kasovic et al. showed that the IronPath app compared with a linear transducer, "recorded significantly lower average concentric velocity values for the front squat and back squat and greater ROM values for the sumo deadlift" [11]. Similarly, Martinez-Cava et al. concluded that "the excessive errors of the newly updated MyLift app advise against use of this tool for velocity-based resistance training" [14]. With that said, other apps as well as experimental software approaches have shown promising results.

In a paper by Pueo et al., they developed a smartphone-based camera system for automatically detecting and tracking a barbell using a custom image-processing algorithm [16]. The algorithm works by creating reference points on the parallel supports of the exercise machine, in this case, a Smith Machine, to segment and compute the barbell position without prior calibration. Their system showed near matching performance with a linear position transducer. That being said, their paper also admitted that the video system is limited by the use of a barbell machine, and does not support free weight barbell movements. Moreover, their system does not include any path tracking and visualization features. Nonetheless, in terms of velocity tracking accuracy, their paper is certainly something to look up to. For the purposes of this project, the main takeaway from this study is the use of colored tape on the barbell to improve accuracy.

Interestingly, two papers by Balsalobre-Fernández et al. concluded that the MyLift (formerly Powerlift) app was in fact a valid and reliable method of tracking barbell velocity [2, 3]. The two studies showed high correlation between MyLift and a linear position transducer. However, a study and subsequent response by Courel-Ibañez et al. contradicted these findings, showing poor reliability from the MyLift app [5]. They also noted that the main author of the two papers where MyLift was validated, is also the main developer of the app. Combined with the aforementioned study by Martinez-Cava et al., that also advised against its use, the MyLift app does not serve as an example of a validated smartphone-based velocity tracker [14].

Ultimately, while linear position transducers deliver incredible accuracy and precision, they are far too expensive to be accessible tools for regular gym-goers and most athletes to use in the gym. Not to mention that linear position transducers also lack in the visualization of barbell path and have the danger of being damaged by the barbell. Unfortunately, due to their consistency, very little work is being done to improve on their flaws. Otherwise, several mobile apps already exist on the market that offer both barbell path and barbell velocity tracking for free. Yet, their inability to track velocity with accuracy and precision makes them unreliable for the practice of velocity based training methods. Pushing this field of technology forward means developing mobile apps with sufficient precision to implement VBT, while maintaining ease-of-use, quality design, and accessibility to a wide audience of gym enthusiasts and athletes.

4 Methods

As a problem of computer vision, the majority of the technical aspects of the project have to do with identifying and then tracking the barbell. We have chosen to use barcode-esque barbell tags which are easily printable and placed on a wide variety of barbells. This is cheap, removes the need to color and/or permanently mark a barbell (that might be for public use), and has been used for other CV applications with great success. Velocity and bar path tracking is involves the constant identification and optical flow estimation of the bar over time. Lastly, our app is designed for use by an iPhone, and as such, we use Swift to implement the app.

4.1 Barbell Identification

Based on a previous project by the April Robotics Laboratory out of the University of Michigan, our barbell identification relies on QR code (fiducial marker) identification [21]. Why QR codes? As low cost is a primary goal of the project, by using QR codes we remove the need for training

novel machine-learning-based barbell identification models while still maintaining increased accuracy. QR codes are easy to generate, cheap and printable, and more efficient to stick/remove from barbells than permanent options (i.e, coloring the barbell). We also considered using brightly colored stickers as our contour, but the use of QR codes nearly guarantees that the correct contour is identified within the frame because of their inner codification. Thus, they are a great candidate for barbell identification.

With the QR codes in mind, the first step is identifying the barbell. We start by printing a QR code based on work by Krogius et al., where they propose a flexible model for generating fiducial markers: "We can generate layouts with a higher data density and smaller border, circular tags, or a custom tag layout with empty space in the middle in which a smaller tag could be placed, allowing this sort of recursive tag to be detected over a large range of distances" [12]. This means we can generate QR codes that fit nicely onto the circular end of a barbell, which typically follow standard dimensions, or at the very least offer easily accessible dimensions in their manuals. For a user, the app will generate and email them a QR code image for them to print. Currently, a user can select a QR code to fit the shaft dimensions of a 2.8cm standard men's Olympic barbell or a 2.5cm standard women's Olympic barbell.

After starting the video recording, the QR code detection follows with two main steps. Firstly, the image is processed via adaptive thresholding, segmenting the current frame by pixel intensity. Contours are extracted from this thresholded image, with special attention paid to only those contours that match the general outline of our marker. This processing essentially encompasses marker candidate detection. Secondly, to determine whether or not the candidates are truly markers, their inner codification is verified. The bits of each marker are extracted, counted (white and black bits), and then checked against a dictionary to determine validity. Fortunately, the barbell is recorded directly parallel, meaning no extra work needs to be done to determine orientation.

4.2 Bar Velocity and Path Tracking

By repeatedly identifying and locating the QR code frame-by-frame, we can track the barbell over time, giving us a path and velocity output. The algorithm begins by initializing, waiting for a QR code to appear in the scene. Since the camera will already be set up to view the barbell and QR code, this process will happen rather quickly. We take that first frame as our original reference. Next, we perform QR code detection as outlined in the above subsection, saving the QR code bounding rect. Continuing, we perform feature matching, that is, we identify the differences in the original frame to next frames, and estimate the optical flow

between the frames. Optical flow is used once again to estimate the bounding rect position of the QR code in the next frame. Lastly, we repeat this process continually until the user ends the video. The contrail of the barbell (the bar path) is relatively straightforward to implement. During the bar localization process, we save the past and current points and as long as they are not null, we compute the thickness and draw a line connecting the points. Velocity tracking similarly takes the past and current location points to determine distance over time. Bar position and velocity metrics are saved continually to be outputted intra-set and for viewing after a set. The output of the velocity and bar path is handled by the app. With that said, the algorithm is complete.

5 Evaluation Metrics

The stated goals of the project are to deliver a cheap, accessible, and accurate velocity and path tracking app for barbell-based exercise. On the whole, QR codes are quite inexpensive to print and only require some form of adhesive to place on a barbell. Thus, the resources necessary to use the app are far less expensive and far more accessible than a linear position transducer. However, our app is slightly more expensive and slightly less accessible than other apps on the market, given that a QR must be printed, whereas other apps require nothing but a phone. Nonetheless, this added cost comes with a much needed increase in accuracy compared to the other apps on the market. We delineate the exact accuracy evaluation metrics in the velocity accuracy subsection. Additionally, we evaluated the ease-of-use and utility of the app via one round of user testing. The specifics are discussed in the app utility subsection.

5.1 Participant Selection

Fifteen users were chosen to participate in a joint evaluation on app utility and app accuracy. Users were made aware of the training design and procedure. No injuries or limitations were reported by any of the participants. All participants were familiar with the exercises used in the study. Lastly, users signed a written informed consent form.

5.2 Study Design

Participants utilized the app for two different exercises: barbell back squat and barbell bench press. For each of the two exercises, participants performed a progressive loading test consisting of increased loads of 15 lbs starting and ending in a range of between 45 lbs and 135 lbs. After each set, participants took 5 minutes of rest to recover and analyze their bar path and velocity metrics outputted from the app. The magnitude of errors and levels of agreement between

the app and a gold standard LPT were calculated for each set for each user.

5.3 Study Methodology

After a familiarization session with the exercises and barbell, participants were allowed time to browse through the app. Participants were asked previously to give their one-repetition maximum to ensure all participants could complete the study with each given weight. Next, participants were asked to perform three repetitions at maximum velocity for each weighted increase with 5 minutes of rest in between. Participants were allowed to set up the phone as they like following guidance from the app. In between sets, participants were allowed to pick up the phone, read and understand the app's output and then place it down once more to continue. During this time, the team recorded the output from the LPT and after the participant was done, from the app as well. Before and after completing the study, participants were surveyed on the following questions.

Pre-study:

1. What features would you expect from a velocity-based training app?

2. What issues do you have with your current training?

3. Have you used a different velocity/bar path tracking app in the past?

Post-study:

1. If you've used a similar app before, how would you compare your experiences?

2. What parts of the app did you find useful?

3. What parts of the app did you NOT find useful?

4. What parts of the app did you find difficult to use?

5. Would you use the app in the future? Why or why not?

6. Are there any additional comments?

Surveys were collected from all 15 participants. Responses were kept anonymous.

5.4 Velocity Accuracy

To evaluate the accuracy of our app, we followed standard convention and employed the use of a linear position transducer. As stated by Janicijevic et al., LPT's, specifically GymAware and T-Force have been validated multiple times in the literature "as gold-standards in studies designed to validate other velocity monitoring devices" [10]. As such, we compared our app to a gold-standard device.

Reliability analysis was completed by calculating the levels of agreement and magnitude of error between the LPT and app for each participant. To ensure reliability was covered for a variety of velocity ranges, we compared results for three velocity segments. These segments are in-line with work by Martinez-Cava et al.[14]: "heavy loads $\geq$ 80% 1RM, MPV $\leq$ 0.50 m/s in BP and 0.70 m/s in SQ), medium loads (50% < 1RM < 80%, MPV between 0.50 and 1.00 m/s in BP and between 0.70 and 1.15 m/s in SQ) and light loads ($\leq$ 50% 1RM, MPV $\geq$ 1.00 m/s in BP and $\geq$ 1.15 m/s in SQ)." Correlation was calculated using the Pearson's correlation coefficient and the intraclass correlation coefficient (ICC). Furthermore, the smallest detectable change (SDC) was calculated using the standard error of measurement (SCD = $\sqrt{2}\times$SEM$\times1.96$). We employed Bland-Altman plots to visualize the agreement along each varying load and velocity segment. Based on previous recommendations, acceptable reliability was set at $ICC > 0.990 and SDC < 0.07 m/s$. [14].

5.5 App Utility

App utility was analyzed using survey results after study completion. Survey's were kept anonymous and after reading responses, key themes and reoccurring mentions were noted from the responses.

6 Ethical Considerations

References

[1] Balsalobre-Fernández, C and Torres-Ronda, L. "The Implementation of Velocity-Based Training Paradigm for Team Sports: Framework, Technologies, Practical Recommendations and Challenges". In: *Sports (Basel)* (2021).

[2] Balsalobre-Fernández, C et al. "Analysis of Wearable and Smartphone-Based Technologies for the Measurement of Barbell Velocity in Different Resistance Training Exercises". In: *Frontiers in Physiology* (2017).

[3] Balsalobre-Fernández, C et al. "Validity and reliability of a novel iPhone app for the measurement of barbell velocity and 1RM on the bench-press exercise". In: *Journal of Sports Sciences* (2018).

[4] Boris, B, Yang, M, and Belongie, S. "Visual Tracking with Online Multiple Instance Learning". In: *Conference on Computer Vision and Pattern Recognition (CVPR)* (2009).

[5] Courel-Ibáñez, J. et al. "Technical Note on the Reliability of the PowerLift App for Velocity-Based Resistance Training Purposes: Response". In: *Annals of Biomedical Engineering* (2020).

[6] Grabner, H, Grabner, M, and Bischof, H. "Real-Time Tracking via On-line Boosting". In: *Proceedings of British Machine Vision Conference (BMVC)* (2006).

[7] He, K et al. "Deep Residual Learning for Image Recognition". In: *Conference on Computer Vision and Pattern Recognition (CVPR)* (2016).

[8] Henriques, J et al. "High-Speed Tracking with Kernelized Correlation Filters". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2015).

[9] Howard, A et al. "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications". In: *ArXiv* (2017).

[10] Janicijevic, Danica et al. "Comparison of the two most commonly used gold-standard velocity monitoring devices (GymAware and T-Force) to assess lifting velocity during the free-weight barbell back squat exercise". In: *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology* 0.0 (2021), p. 17543371211029614. DOI: 10.1177/17543371211029614. URL: https://doi.org/10.1177/17543371211029614.

[11] Kasovic, J et al. "Agreement Between the Iron Path App and a Linear Position Transducer for Measuring Average Concentric Velocity and Range of Motion of Barbell Exercises". In: *Journal of Strength and Conditioning Research* (2021).

[12] Krogius, M., Haggenmiller, A., and Olson, E. *Flexible Layouts for Fiducial Tags*. 2019.

[13] Liu, W et al. "SSD: Single Shot MultiBox Detector". In: *Computing Research Repository (CoRR)* (2015).

[14] Martínez-Cava, A et al. "Reliability of technologies to measure the barbell velocity: Implications for monitoring resistance training". In: *PLOS One* (2020).

[15] Pérez Castilla, A et al. "Reliability and Concurrent Validity of Seven Commercially Available Devices for the Assessment of Movement Velocity at Different Intensities During the Bench Press". In: *The Journal of Strength and Conditioning Research* (2019).

[16] Pueo, B et al. "Video-Based System for Automatic Measurement of Barbell Velocity in Back Squat". In: *Sensors (Basel)* (2021).

[17] Redmon, J et al. "You Only Look Once: Unified, Real-Time Object Detection". In: *CoRR* (2015).

[18] Ren, S et al. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". In: *CoRR* abs/1506.01497 (2015).

[19] Simonyan, K and Zisserman, A. "Very Deep Convolutional Networks For Large-Scale Image Recognition". In: (2015).

[20] Wadhi, T et al. "Validity and Reliability of the GymAware Linear Position Transducer for Squat Jump and Counter-Movement Jump Height". In: *Sports (Basel)* (2018).

[21] Wang, J. and Olson, E. *AprilTag 2: Efficient and robust fiducial detection*. 2016.

[22] Weakley, J et al. "Velocity-Based Training: From Theory to Application". In: *Strength and Conditioning Journal* (2021).